IMPROVED PERSONALISED DATA MODELLING USING PARAMETER INDEPENDENT FUZZY WEIGHTED K-NEAREST NEIGHBOUR FOR SPATIO/SPECTRO-TEMPORAL DATA

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I hereby declare that the work in this project report is my own except for quotations and summaries which I have duly acknowledged.

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To my beloved Mama and Abah.

To my brothers and sisters.

Les préférences, Noureen Talpur.

Thanks for being there and appreciating those little things.

Though Absent You Are Always Near

Still Loved, Still Missed, Still Very Dear

You Are an Inspiration to All–Tok Ayah

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ABSTRACT

Machine learning technologies have been growing rapidly in recent years. Researchers have come up with several data processing architectures, enabling machines to consume, interpret, and produce understandable output from real-world data to improve the quality of our lives. The NeuCube architecture is a data processing architecture for spatio/spectro-temporal data which consists of four main modules: a spike encoding module, a recurrent SNN reservoir, an output module, and an optimization module. Despite it has been utilised on many various applications, most improvement of the architecture focuses on user experience rather than improving the result accuracy. Upon exploration of the architecture, the weighted *k*-nearest neighbours algorithm used for the classification module is found to be prone to misclassification as it relies solely on the majority voting rule to determine the class for new data vector. Additionally, it does not consider the class-specific fuzzy weight information during the classification process. Therefore, a data modelling mechanism which implements PIfw*k*NN classifier algorithm for improving the overall classification accuracy of the NeuCube architecture has been proposed. The proposed data modelling applies an additional class-specific fuzzy weight information to new data vectors during the classification process. In this research, the optimal parameters set for experiments has also been identified. The approach has been validated by using the Kuala Krai Rainfall Dataset, Dow Jones Index Data Set, and Gold Price and Performance Dataset for the 3-days earlier and 1-day earlier event prediction. From the experiments, the improved personalised data modelling using PIfw*k*NN classifier has shown a significant increase in terms of overall classification accuracy as compared to the conventional MLP, f*k*NN, and NeuCube with w*k*NN classifier.

ABSTRAK

Saban tahun, teknologi pembelajaran mesin telah berkembang dengan pantas. Para penyelidik telah menghasilkan beberapa seni bina pemprosesan data yang membolehkan mesin menerima, mentafsir, dan menjana output dari data dunia nyata bagi tujuan memperbaik taraf hidup kita. NeuCube merupakan sebuah seni bina pemprosesan data bagi data berbentuk spatio/spectro-temporal yang mengandungi empat modul utama yakni: modul pengekodan lonjakan, takungan SNN berulang, modul output, dan modul pengoptimum. Walaupun telah digunakan secara meluas, sebahagian besar fokus penambahbaikan seni bina ini menjurus pada pengalaman pengguna berbanding bagi meningkatkan ketepatan hasil. Melalui penerokaan, telah didapati bahawa algoritma *weighted k-nearest neighbours* yang digunakan dalam modul klasifikasi terdedah kepada ralat pengelasan atas sebab proses pengelasan tersebut bergantung sepenuhnya terhadap *majority voting rule* bagi menentukan kelas bagi vektor data baru. Tambahan, algoritma tersebut tidak mengambil kira pemberat fuzzy kelas khusus semasa proses klasifikasi. Justeru, sebuah mekanisma pemodelan data menggunakan pengkelas PIfw*k*NN telah dicadangkan bagi menggantikan pengelas sedia ada bagi menambah baik ketepatan proses pengelasan data. Kaedah yang dicadangkan ini menggunakan maklumat pemberat fuzzy kelas khusus terhadap data baharu semasa proses pengkelasan dilaksanakan. Dalam penyelidikan ini, parameter optimal bagi menjalankan eksperimen juga telah dikenalpasti. Kaedah ini telah disahkan menggunakan Dataset Taburan Hujan Kuala Krai, Dataset Indeks Dow Jones, dan Dataset Prestasi Harga Emas bagi jangkaan seawal 3-hari sebelum dan 1-hari sebelum berlakunya sesuatu kejadian. Melalui eksperimen tersebut, kaedah menggunakan NeuCube beserta pengelas PIfw*k*NN telah memaparkan peningkatan yang signifikan dari sudut ketepatan pengelasan secara keseluruhan jika dibandingkan dengan kaedah konvesional MLP, f*k*NN, dan NeuCube beserta pengelas w*k*NN.

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LIST OF SYMBOLS AND ABBREVIATIONS

AER	-	Address-Event-Representation
eSNN	-	evolving Spiking Neural Network
eSTDM	-	evolving Spatio-Temporal Data Modelling
*k*NN	-	*k*-Nearest Neighbours
f*k*NN	-	Fuzzy *k*-Nearest Neighbour
w*k*NN	-	Weighted *k*-Nearest Neighbour
PIfw*k*NN	-	Parameter Independent Fuzzy Weighted *k*-NN
HPC-EC	-	Hippocampal-entorhinal cortex
LOOCV	-	Leave-One-Out Cross-Validation
MLP	-	Multilayer Perceptron
PMeSNNr	-	Personalised Modelling evolving Spiking Neural Network Reservoir
PSP	-	Postsynaptic Potential
RNN	-	Recurrent neural network
SNN	-	Spiking Neural Network
SNNr	-	Spiking Neural Network Reservoir
SSTD	-	Spatio/Spectro-Temporal Data
STDP	-	Spiking Time Dependent Plasticity
SVM	-	Support Vector Machine
UCIMLR	-	University of California Irvine Machine Learning Repository

LIST OF PUBLICATIONS

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CHAPTER 1

INTRODUCTION

1.1 Research background

Early event prediction is made possible by analysing patterns in event occurrences given that sufficient knowledge of previous similar occurrences is provided. Such analysis is required in assisting government and non-government organisations in formulating an early prediction system, which is capable of providing an early alert towards the risk of a natural disaster such as the risk of flood occurrence, which happens every year in certain areas of Malaysia. To come up with such a sophisticated system, a detection mechanism needs to be addressed, where it consumes real-world data for training, validating, and optimization of a prediction model over time.

Most of the time, real-world data such as environmental data and ecological data is needed to be presented in the form of spatio/spectro-temporal data (SSTD) as it captures measurements of all variables within the environment on time (include temporal component). For instance, all environmental-related variables, which contribute to the risk of flooding is captured every few hours and are represented in the form of SSTD. Therefore, by having these variables measured over time, the prediction system can capture the interrelationship between the variables over time. Next, the optimised and validated prediction model is useful for application in the real world for predicting the probability and the risk of events occurrences, such as flood prediction. In this research, a case study of flood risk assessment is adapted for creating an improved personalised data modelling by analysing the environmental data collected in the form of SSTD to create an earlier risk assessment for flood risk occurrence.

Two reasoning theories that can be applied for creating data models are inductive reasoning and transductive reasoning. Inductive reasoning creates a generalised model from the entire set of historical data while transductive reasoning creates a model based on historical data and adapts new data to improve the existing model. In most cases, inductive reasoning is sufficient; however, transductive reasoning is more suitable for individual or personalised cases, such as situations related to clinical and medical conditions, geological problems, or weather and disaster prediction. Most of the data related to the environment are in the form of complex SSTD, which requires pre-processing so that it is compatible to be fed to the network.

Global modelling, local modelling, and personalised modelling are introduced based on the previously discussed reasoning theories [1]. Global modelling is created from the entire problem space, hence offers a general interpretation of the data [1], [2]. Global models are however not suitable for problems with a dynamic environment as the model does not evolve based on the new data [1], [2]. Local modelling aims to solve the adaptive issue of global models (mostly are based on clustering techniques), hence providing more adaptable behaviour to new data vectors [1]. Personalised modelling, on the other hand, creates a model for only a single data vector in a local domain [2].

Through a series of studies, Kasabov *et al*. [3]–[6] has introduced the NeuCube architecture for mapping and learning neuronal spikes from SSTD. The architecture has been implemented on various applications such as for understanding brain data [4], [7], [8], solving ecological problems [6], [9], stroke risk prediction [3], [10], [11], video and audio pattern recognition [12], [13], and flood risk assessment [14], [15]. The studies and implementation have provided promising results produced by the architecture. Despite being able to produce a result with high accuracy, the mechanism of classification in the NeuCube architecture is prone to misclassification as it utilises the weighted *k*-nearest neighbour (w*k*NN), which relies solely on the majority voting rule to determine the class during the classification process [3], [4], [10]. The w*k*NN classifier does not consider the membership of each new data vector in contribution towards the actual class.

Therefore, this work attempts to provide improved personalised data modelling by employing a parameter independent fuzzy weighted *k*-nearest neighbour (PIfw*k*NN) for SSTD. The PIfw*k*NN classifier utilises class-specific weights information during the classification process, therefore providing a clear advantage towards the mechanism of constructing the personalised data model. Several techniques incorporating spiking neural networks (SNN) methods are explored, compared, and contrasted, whereby a suitable approach is validated with real-world flood event data and other benchmark datasets.

1.2 Problem statement

Among many soft-computing and machine learning algorithms existing today, spiking neural network has gained popularity due to its capability to encode hidden patterns between variables and time [2]. A novel NeuCube architecture [3] consisting of an evolving spiking neural network (eSNN) mechanism for personalised modelling method has been introduced to process and analyze SSTD. The architecture has been implemented in various applications including for understanding brain data [4], [7], [8], solving ecological problems [6], [9], stroke risk prediction [3], [10], [11], video and audio pattern recognition [12], [13], as well as flood risk assessment [14], [15]. In a study conducted by Capecci *et al.* [7], the NeuCube architecture has been used for the prediction of response towards treatments and drug dosage effects using trained EEG data on the created model. Most of the NeuCube implementation papers have presented that the architecture is capable of producing a higher accuracy result as compared to using traditional statistical and artificial intelligence methods. However, upon the exploration of the framework, shortcomings have been found in the classifier module.

Previously, based on the existing NeuCube architecture, the output was classified solely based on majority voting rule according to the weighted *k*-nearest neighbours for a classification task [3], [4], [10]. Albeit the one-pass learning offered in NeuCube is relatively fast and suitable for SSTD processing [11], the neurons may be inaccurately labelled due to a lack of references to the similar neighbouring neurons. The w*k*NN classifier used in the existing NeuCube architecture does not consider the membership of each variable in contribution to the correct class. There is a risk of incorrect classification due to neglecting the known class-specific weight during the classification process. On the other hand, the proposed PIfw*k*NN classifier can solve this issue as it considers class-specific weight during the classification process. By considering the known class-specific weights during classification, improved overall classification accuracy can be produced since the network utilized an additional reliable knowledge to create a more reliable information-based network.

The second drawback of the existing w*k*NN classifier is that it cannot assign fuzzy membership value to each of the new and existing data vectors; therefore, the selection of class for the new data vector is made in Boolean (0 or 1). This means each data vector can only belong to one class, regardless of its actual membership to another class. Due to this situation, the result generated by the current classifier is misrepresented, as the degree of membership of each data vector is not taken into account during the classification process. By implementing the PIfw*k*NN algorithm, the classifier can apply fuzzy membership allowing each data vector to have membership degree to multiple classes, therefore, allowing the data vector to be assigned to a class where it is related.

Third, to create an optimal network, there is a challenge to fine-tune all parameters during the training and validation of the personalised data model. It is necessary to fine-tune all parameters for the experimentation to produce the highest accuracy result at the earliest time possible without overfitting the network. Therefore, finding all optimised parameters for creating a personalised model is a challenge this research will tackle.

There is no doubt that NeuCube architecture is useful for predicting and classifying data across different domains. Applying an algorithm such as PIfw*k*NN produces a more reliable knowledge by associating class-specific weights (which act as membership functions) for a better classification rather than solely depend on the majority voting for assigning classes. The proposed PIfw*k*NN algorithm combines both the capability of fuzzy membership with the majority voting rule for assigning classes more accurately. This research introduces an interest to create improved personalised data modelling using PIfw*k*NN for SSTD to improve overall classification accuracy.

To summarise, the statement of problems is *"The current wkNN classifier in the NeuCube architecture executes classification solely based on the majority voting rule based on the selected nearest neighbours, without considering the membership of each* *new data vector in contribution towards to the actual class. Therefore, given the complex dimension of the SSTD, the challenge is to propose and justify a suitable classifier, which can produce a higher overall accuracy as compared to the existing wkNN classifier used in the NeuCube architecture without losing the valuable information. It can be executed within the spatial and temporal component of the data by considering the interrelationship between both components during the process.''*

1.3 Objectives

This research embarks the following objectives:

i. To propose a data modelling, which implements PIfw*k*NN classifier algorithm for improving the overall classification accuracy of the NeuCube architecture.
ii. To find optimal parameters for the improved personalized data modelling utilizing PIfw*k*NN classifier.
iii. To evaluate and compare the performance of the personalised data modelling with PIfw*k*NN classifier against the existing w*k*NN classifier, MLP, and f*k*NN classifier in terms of classification accuracy.

1.4 Scope of research

This study is limited to an investigation of a suitable classifier for the existing NeuCube framework, allowing the architecture to produce a better accuracy classification result as compared to the existing classifier. The dataset used is taken from a real-world case study data which covers Kuala Krai historical environmental data from 2012-2016 (5 years) provided by the Malaysian Meteorological Department.

1.5 Significance of research

This research contributes to the body of knowledge in terms of providing a much suitable algorithm to be used in the NeuCube architecture, which utilizes eSNN engine. This research presents an improvement of overall classification result accuracy by implementing the proposed PIfw*k*NN classifier. The proposed PIfw*k*NN classifier is capable of producing a higher classification accuracy result by allowing each data vector to have a specific-class fuzzy weight. Therefore, the determination of the class for new data vectors considers the fuzzy membership value as well; instead of only being determined by the majority voting rule based on the *k*-nearest neighbour.

In the real world, the ability to produce personalised data models can be applied to environmental cases and benefit society with the development of an event management system. The research outcome can be implemented in the disaster alert system, where the engine of the alert system is capable of predicting the risk of environmental disasters such as floods, tsunami, earthquakes, and many others. The development of such technology could help to reduce the risk of accidental death and property losses by providing an earlier alert to be broadcast to a high-risk area. Another possible application of this research is to integrate it into the Disaster Management Decision Support System for property valuation in the flood-affected area; the system can analyse contributing factors in assessing the value of the property depending on the risk prediction of the flood event.

The implications of the results produced by this method are significant in terms of environmental disaster management. This method presents opportunities for other applications such as healthcare management, financial projection, image processing, and many others. The important thing is that this architecture reveals the maximum potential and usefulness of this architecture for modelling data in an integrated manner.

1.6 Thesis organisation

This thesis comprises the following contents:

i. ***Chapter 1: Introduction.*** This chapter contains the research background, motivation, objectives to achieve, scope, and significance of the study.

ii. ***Chapter 2: Literature review.*** This chapter reviews neural network models, explains the predictability of the environmental events, reasoning theory, data modelling approaches, suitable classification algorithms, and other related works.

iii. ***Chapter 3: Research methodology.*** This chapter discusses the research phases, research framework, dataset collection, and data treatment, as well as the proposed approach for experimentation.

iv. ***Chapter 4: Results and analysis.*** Presents each case studies and their corresponding experimental result, analyses, and discusses the result; including tangible and intangible factors that may be affecting the result.

v. ***Chapter 5: Conclusion and future works.*** This chapter summarises and concludes the proposed work and provides recommendations for future continuation of work.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter elaborates on the evolution of neural networks and their generations. It also introduces environmental events occurrences patterns and nature of environmental-related data, and data patterns existing in nature. Along with this chapter, reasoning approaches and data modelling approaches are presented. Finally, suitable classification algorithms for the eSNN architecture are presented and justified.

2.2 History of neural networks

The neural network is a collection of computational units (each referred to as a neuron or a perceptron) that are interlinked and may reside within a large system [16]. The artificial neural network has been inspired by the biological neural network mechanism [16]; designed to mimic its physiological behaviour hence allowing the network to replicate the decision-making capability of a biological brain.

In a series of five studies by Hodgkin and Huxley between 1951 and 1952 [17]–[21], the authors have explained the working mechanism of Hodgkin-Huxley model which is designed after an observation of the spikes and movement of action potentials (in the form of ions) in an axon of a giant squid. This is the first work that has used a mathematical model to explain the biological mechanism and has inspired many researchers to expand

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